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HotM2 article or Protocol



# State of emergency and human mobility during the COVID-19 pandemic in Japan

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## ABSTRACT

**Introduction:** The Japanese government declared a state of emergency (SoE) to control the spread of the coronavirus disease (COVID-19). However, the requirements of these SoE were less stringent than those in other nations. It has not been assessed whether soft containment policies were sufficiently effective in the promotion of social distancing or the reduction of human contact.

**Methods:** Mobility changes across different travel destinations, such as, (a) retail and recreation spaces; (b) supermarkets and pharmacies; (c) parks; (d) public transportation; (e) workplaces; and (f) residential areas, were analysed using the Google mobility index to assess social distancing behaviour in all Japanese prefectures between 15 February 2020 and 21 September 2021. The changes were evaluated through the utilisation of an interrupted time-series analysis after adjustment for seasonality and various prefecture-specific fixed-effects, and distinguishment of potential heterogeneity across multiple SoEs and the time that had passed after the declaration. **Results:** The mobility index for retail and recreation exhibited an immediate decline of 7.94 percent-points (95%CI: -8.77 to -7.12) after the declaration of the SoE, and a further decline after the initial period (beta: -1.27 95%CI: -1.43 to -1.11). However, it gradually increased by 0.03 percent-points (95%CI: 0.02–0.03). This trend was similar for mobility in other places. Among the four SoEs, the overall decline in human mobility outside the home was the least significant in the third and fourth SoE, which suggests that people were less compliant with social distancing measures during these periods.

**Conclusions:** Although government responses to the pandemic may aid the controlling of human mobility outside the home, their effectiveness may decrease if these interventions are repeated and enforced for extended periods. A combination of these with other measures (i.e. risk-communication strategies) would enable even mild containment and closure policies to effectively curb the spread of the virus.

## 1. Introduction

Given its enormous impact on population health, society, and economy, national governments implemented large scale public health interventions (i.e. lockdowns and state of emergency [SoE] declarations) to respond to and control the spread of the COVID-19 virus (Hsiang et al., 2020). Through public health interventions, individuals and businesses were required to refrain from nonessential

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activities and asked to practise social distancing, which led to an economic downturn due to the restricted opportunities for consumption and production (Guan et al., 2020; Verschuur et al., 2021).

With the absence of herd immunity and/or other effective treatments, the minimisation of transmission through other means, such as mask wearing, disinfection, ventilation, and physical distancing, are important. Human mobility, in terms of the tracing of social distancing and human contact in places such as shops, restaurants, and workplaces, was a useful indicator for the prediction of COVID-19 outbreaks (Badr et al., 2020; Chinazzi et al., 2020; Kraemer et al., 2020; Nagata et al., 2021; Nouvellet et al., 2021). Thus, changes in human mobility can be tracer indicators (i.e. surrogate parameters for the effectiveness of a policy that aims to curb the virus spread) of the general public's response to government directives with regard to the virus. This is because they are relatively easy to capture through the use of location information (e.g. mobile phones with a Global Positioning System) as compared to other metrics (e.g. proportion of individuals wearing masks or disinfecting their hands regularly).

Previous studies that assessed mobility trends during the COVID-19 pandemic in specific regions of Japan and Italy, national trends in Germany, and global trends, have revealed that containment and closure policies, such as country lockdowns and SoE declarations effectively reduce human mobility (Arimura et al., 2020; Hale et al., 2021; Schlosser et al., 2020; Vinceti et al., 2020; Yabe et al., 2020). However, a study in Argentina observed that extended restriction without complementary mitigation measures (e.g. business closure and home isolation) could become ineffective given the economic and social costs that it entails (Larrosa, 2021). While tighter restrictions (e.g. lockdown and curfew) can decrease mobility, it could lead to a deeper economic downturn due to the decrease in economic activity. Moreover, apart from these tighter non-pharmaceutical interventions, milder interventions such as risk communication strategies were also found to be effective in the reduction of the spread of infection (Haug et al., 2020). These risk strategies include the information provided by the government, primarily through social media, to encourage people to stay at home, and self-quarantine and maintain social distancing if one develops symptoms. As was learnt from Wuhan in China, effective risk communication should integrate the accessibility and transparency of risk information and the appropriate timing and frequency of communication (Zhang et al., 2020). To efficiently curb the virus spread, an ideal stringency of non-pharmaceutical interventions should be implemented. Meanwhile, the adopted countermeasures against the pandemic by each country highly depend on local governance and socio-economic and cultural orientations (Shaw et al., 2020; Yan et al., 2020).

In Japan, the government responses to the pandemic are less stringent compared to those of other countries (University of Oxford, 2021). The government focused on requesting, rather than mandating, individuals and businesses to practise social distancing and avoid nonessential activities even under a SoE. Nevertheless, human mobility was still effectively reduced in specific urban cities (Arimura et al., 2020; Yabe et al., 2020). Thus, Japan's experiences with COVID-19 countermeasures can be helpful in the mitigation of the spread of the virus by the reduction of human mobility with less strict interventions. Although lockdowns and SoEs have demonstrated effectiveness in the reduction of human mobility (Arimura et al., 2020; Hale et al., 2021; Schlosser et al., 2020; Vinceti et al., 2020; Yabe et al., 2020), little is known about whether longer and repeated 'alerts' that use risk communication strategies to request citizens to avoid nonessential activities are equally effective.

A situation in which people are requested to voluntarily engage in social distancing behaviours may make it difficult for them to comply repeatedly and for extended periods. According to the Health Belief Model (Carico et al., 2021), individual beliefs with regard to the virus (e.g. susceptibility and severity) and preventive behaviours (e.g. effectiveness, barriers, and self-efficacy) affect an individual's actual social distancing behaviour. Individuals could become more optimistic to the infection due to heuristics biases (Tversky and Kahneman, 1974) after being subjected to a SoE multiple times, which may lead to their engagement in higher-risk behaviours.

This study aims to evaluate the association between SoE declarations and human mobility through the use of data from all prefectures in Japan. This study hypothesises that SoEs reduce people's mobility outside the home (e.g. retail and recreation) and increase the time spent at home. Meanwhile, by repeated and longer durations of SoEs, individuals may become more optimistic towards the infection, and thereby become less compliant with government orders and demonstrate non-decreased outdoor mobility even during the SoE.

## 2. Methods

### 2.1. Data

#### (1) Human mobility

A human mobility index published by Google (hereafter referred to as the 'mobility index') was used to track one of the indicators that affect COVID-19 transmissibility (Hale et al., 2021). The mobility index, which measures visits and the length of stay at various places, represents changes across each day from the baseline (i.e. the median value of the same day of the week between 3 January - 6 February 2020). The outbreak was yet to occur in Japan during this baseline period; by 6 February 2020, only a total of 17 cases were confirmed. This daily index is available for all the 47 prefectures in Japan and covers the following six categories: (a) retail and recreation spaces; (b) supermarkets and pharmacies; (c) parks; (d) public transportation; (e) workplaces; and (f) residential areas. Of these six categories, (a) retail and recreation spaces and (c) parks could be considered as places for leisure activities, while visits to (b) supermarkets and pharmacies can be considered essential trips. Stay-at-home or work-from-home behaviours of the citizens can be observed in the (d) public transport, (e) workplaces, and (f) residential categories. The mobility index from the baseline (between 3 January - 6 February 2020) up to 21 September 2021, which included the latest data that were available when this study was conducted, was analysed in this study. The dataset includes a total of 27,495 observations from 47 prefectures and includes some missing

observations for some mobility indices.

## (2) State of Emergency

To analyse the effects of SoEs on human mobility, a dummy variable that indicated the SoE status for each prefecture was created. In response to the drastic virus spread, the Japanese government declared an SoE four times and requested residents to refrain from nonessential activities in prefectures wherein the spread of the infection was serious and healthcare capacities were under strain. Consequently, during the SoE, the national government asked individuals, business owners, and organisations to comply with five main requests in addition to basic infection controls such as mask wearing and disinfection. These included: 1) restrictions on restaurants (e.g. shortened business hours and no alcohol service); 2) restrictions on facility use; 3) restrictions on events (e.g. limited number of participants); 4) pause on non-essential outing and travels; and 5) furtherance of work-from-home and staggered work schedules. The first nationwide SoE was declared in seven prefectures from 7 April to 25 May 2020, before it expanded to all other prefectures. The second SoE was longer than the first and was declared in 11 prefectures located in urban areas from 8 January to 21 March 2021. The third SoE began on 25 April 2021 in four prefectures, and then expanded to five other prefectures. The third SoE was lifted on 20 June 2021 for all prefectures except for one. The fourth SoE was declared on 12 July 2021 in Tokyo, following which it expanded to 17 other prefectures. The timelines of each SoE are described in Appendix Note 1.

## (3) Policy tracker

To quantify the stringency of government responses to the pandemic, a research group from the University of Oxford published a ‘stringency index’, which comprised containment and closure policies and public information campaigns, and was reportedly associated with human mobility (Hale et al., 2021). This index, in addition to the SoE, was used to evaluate the association of government responses with population behaviours in Japan. As illustrated in Appendix Fig. 1, the stringency index of Japan increased during the SoEs, and generally corresponded to the waves of the spread of the infection.

## (4) Household consumption

Stronger government interventions to control the spread of the virus may lead to the decrease in individual economic activity, which can worsen the effects on the economy. While individual-level monthly data on economic activity is not publicly available, the Japanese government publishes monthly statistics on average household consumption based from a nationwide sample of approximately 7,900 households (Statistics Bureau, 2021). Therefore, the monthly average of household consumption was used as an indicator of the economic activities of the citizen. To adjust for the seasonality, percentage changes from the past three-year averages of the same month were calculated. Further details on the data used in this study are presented in Appendix Note 2. Ethical approval was not required as this study was based on the secondary analysis of publicly available data.

## 3. Empirical strategy

### 3.1. Detrending the mobility index

The mobility index was used as the tracer indicator of the transmissibility of COVID-19 in this study. However, human mobility is largely affected by various factors, such as weather conditions, day of the week, national holidays, and other specific events, which can differ across regions. Therefore, since simple intertemporal comparisons (e.g. pre-post and past-present comparisons) can generate bias, the mobility index could only be utilised after the effects of weather conditions and location-specific seasonality were removed. With this, the mobility index was detrended following the obtainment of the residuals ( $e_{i,t}$ ) between the actual values and the fitted values as expressed in equation (1) and (2):

$$e_{i,t} = Y_{i,t} - \tilde{Y}_{i,t} \quad (1)$$

$$\tilde{Y}_{i,t} = \alpha_w \text{Weather}_{i,t} + \gamma_i + \delta_{i,h} + \eta_{i,d} + \varepsilon_{i,m} + \mu_{i,y} \quad (2)$$

Where  $Y_{i,t}$  denotes the actual mobility index of prefecture  $i$  on the date  $t$ .  $\tilde{Y}_{i,t}$  represents the linear fitted value of the mobility index predicted by daily weather conditions (i.e. mean temperature, total precipitation, sunshine duration, total snowfall, and mean wind speed), prefecture-specific fixed-effects ( $\gamma_i$ ), prefecture-by-national-holiday fixed-effects ( $\delta_{i,h}$ ), prefecture-by-day-of-the-week fixed-effects ( $\eta_{i,d}$ ), prefecture-by-month fixed-effects ( $\varepsilon_{i,m}$ ), and prefecture-by-year fixed-effects ( $\mu_{i,y}$ ). Intuitively,  $e_{i,t}$  expresses a human mobility pattern that is not explained by weather conditions and prefecture-specific calendar effects.

### 3.2. State of emergency and human mobility

To evaluate the association between a SoE and human mobility, several models were estimated in this study. First, the average effects of the SoE were obtained by the estimation of the following equation (3):

$$e_{i,t} = \beta_0 + \alpha_0 SoE_{i,t} + \tau_o \sum_{t=7}^{t-1} \frac{covid_{i,t}}{7} + \gamma_i + \delta_{i,h} + \eta_{i,d} + \varepsilon_{i,m} + \mu_{i,y} \quad (3)$$

Where  $\beta_0$  is the constant and  $\alpha_0$  represents the parameter to be estimated for the quantification of percent changes from the baseline during the SoE—a dummy variable that indicates the state of emergency periods (coded 1) or not (coded 0)—of the detrended mobility index. Per-day infections confirmed in the past seven days for each prefecture were included in the model to control potential changes in population behaviours due to the existing conditions. The same by-prefecture fixed-effects presented in equation (2) are also included. Moreover, the following equation (4) was estimated to assess heterogeneity in multiple SoEs:

$$e_{i,t} = \beta_0 + \alpha_1 First_{i,t} + \alpha_2 Second_{i,t} + \alpha_3 Third_{i,t} + \alpha_4 Fourth_{i,t} + \alpha_5 \sum_{t=7}^{t-1} \frac{covid_{i,t}}{7} + \gamma_i + \delta_{i,h} + \eta_{i,d} + \varepsilon_{i,m} + \mu_{i,y} \quad (4)$$

Where each  $\alpha_1$ ,  $\alpha_2$ ,  $\alpha_3$ , and  $\alpha_4$  represents the mobility changes in the first, second, third, and fourth SoE, respectively.

To solidify the understanding of the association between the SoE and mobility changes, an interrupted time series analysis (Bernal et al., 2017) was conducted by the estimation of the following equation (5):

$$e_{i,t} = \theta_0 + \theta_1 Time_t + \theta_2 SoE_{i,t} + \theta_3 SoE_{i,t} \times Time_{SoE} + \theta_4 \sum_{t=7}^{t-1} \frac{covid_{i,t}}{7} + \gamma_i + \delta_{i,h} + \eta_{i,d} + \varepsilon_{i,m} + \mu_{i,y} \quad (5)$$

Where  $Time_t$  represents the number of days since the beginning of the study and  $Time_{SoE}$  represents the number of days since the beginning of the SoE. Additionally,  $\theta_1$  indicates the underlying pre-intervention trend,  $\theta_2$  is the level of change that followed the SoE, and  $\theta_3$  denotes the slope change that followed the SoE. An extension of equation (4) in the same manner as equations (3) and (5) enabled the evaluation of the mobility changes associated with each SoE by the time interrupted series analysis. To account for potential heteroskedasticity and autocorrelation, prefecture-level clustered standard errors were estimated by the panel data linear regression models with high-dimensional fixed effects (Correia, 2016a, b). Additionally, all estimates were weighted by the total population of each prefecture. Furthermore, potential non-linear time trends were assessed for each model, and thus assumed a quadratic trend.

### 3.3. Government responses, mobility, and economic activity

The stringencies of containment and closure policies differ across regions on the basis of COVID-19 conditions; however, only a national level index was available. Therefore, country-level analyses were conducted to assess the daily association between the stringency index and human mobility. Given that only the monthly averages for the whole country were available, the association between the stringency index and consumption was visualised.

**Table 1**  
Descriptive statistics.

Variable	Observations (Prefecture-day)	Mean	Standard deviation
Weather			
Temperature (°C)	27,495	17.39	8.23
Precipitation (mm)	27,495	5.63	15.71
Sunshine duration (hours)	27,495	0.13	1.35
Snowfall (cm)	27,495	5.55	4.19
Wind speed (m/s)	27,495	2.89	1.33
Mobility (%)			
Retail and recreation	27,495	−9.37	11.25
Grocery and pharmacies	27,495	1.62	6.57
Parks	27,126	−0.47	27.35
Public transport	27,480	−22.42	14.41
Workplaces	27,495	−11.90	13.49
Residential area	27,495	5.86	4.52
Per-day infections	27,495	60.98	235.44
SoE (days if SoE = 1)			
Aggregated	3,174	36.82	9.01
First	1,502	33.34	7.72
Second	614	58.84	13.49
Third	517	58.58	22.66
Fourth	642	38.45	10.54
Total population	27,495	2,684,404	2,750,039

Note: Descriptive statistics for 47 prefectures between 15 February 2020 and 24 July 2021 is shown in this table. SoE = State of Emergency; 47 prefectures were included in the first SoE, 11 in the second, 10 in the third and 18 in the fourth SoE. The third and fourth SoE were still ongoing at the end of the study period, thus the number of days is right-censored.

### 3.4. Additional analyses

Several additional analyses were conducted to assess various factors that may contribute to mobility trends and/or effects of the SoE. First, the effects of the quasi-SoE were assessed; because, in addition to SoEs, the government declared a quasi-SoE when the infection conditions were moderately severe. Second, the heterogeneous effects of SoEs on human mobility trends by the number of infections confirmed in each prefecture were analysed, taking note that the mobility trends may differ across regions based on COVID-19 conditions. Third, as the effects of the SoE may depend on the people's trust in the government, an additional analysis was conducted to evaluate whether such trust mattered to human mobility trends. Fourth, COVID-19 vaccination rates were taken into account to assess the effects of the SoE on mobility, as the increase in vaccination rates may attenuate the effectiveness of the SoE. All analyses were conducted by the Stata software version 17.0 (StataCorp LLC, College Station, USA).

## 4. Results

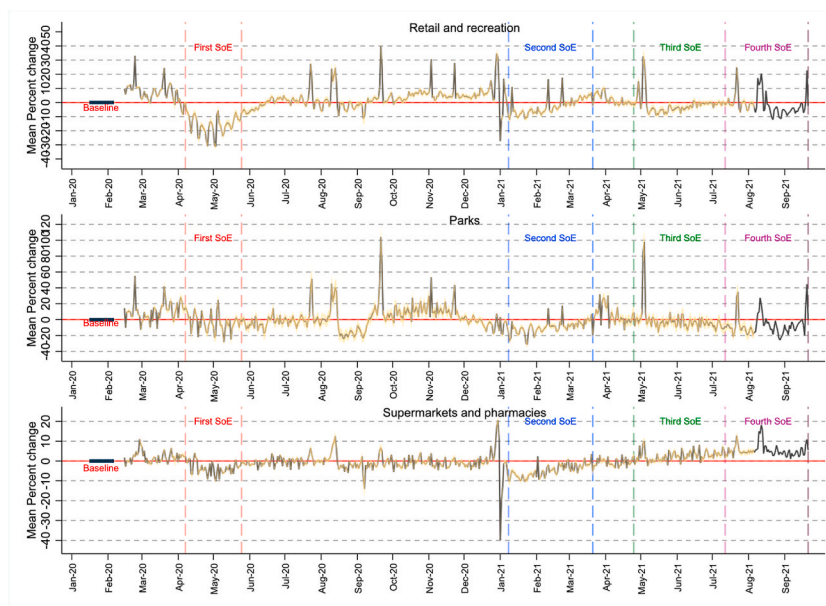
### 4.1. Descriptive statistics

Descriptive statistics on key variables used in this study are presented in Table 1. The study covers all prefectures in Japan between 15 February 2020 and 21 September 2021, and around 27,495 prefecture-day observations were available. Since the four seasons are distinct in Japan, the per-day mean temperature, precipitation, and sunshine duration fluctuate throughout the seasons.

As for human mobility, mean percentage changes in the number of users of retail and recreation spaces ( $-9.37$ , standard deviation [SD]:  $11.25$ ), public transport ( $-22.42$ , SD:  $14.41$ ), and workplaces ( $-11.90$ , SD:  $13.49$ ) were negative during the study period compared to the baseline, while the one for residential spaces was positive ( $5.86$ , SD:  $4.52$ ). Mobility in terms of visits to groceries and pharmacies, and parks demonstrated a less than or around 1% change on average.

The average duration of the first SoE, which was effected in all prefectures, was 33.34 days (SD: 7.72). In contrast, the other SoEs were declared only in regions where the virus spread was particularly severe and healthcare capacities were under strain. The second SoE was the longest among the three, and lasted 58.84 days on an average (SD: 13.49), while the third and fourth SoEs continued until the end of the study period and lasted 58.58 days (SD: 22.66) and 38.45 (SD: 10.54) days on average, respectively.

Fig. 1 illustrates the descriptive presentations of the detrended mobility for retail and recreation spaces, parks, supermarkets, and pharmacies. With regard to mobility in terms of retail and recreation spaces, a remarkable decline in mobility was observed during the first SoE; however, it was less obvious in the succeeding SoEs. Fig. 2 also presents mobilities related to self-quarantine, such as work-from-home and stay-at-home behaviours. During the first SoE, people visibly avoided the use of public transportation, worked from



Note: Relative percentage changes from the baseline day (median value from 3 Jan – 6 Feb 2020), controlling for weather conditions and time-location-fixed effects. SoE = State of Emergency; Mean percentage change from baseline with shaded areas representing 95%CI among 47 prefectures. The SoE periods denote time ranges where the declaration took effect in at least one prefecture.

**Fig. 1.** Descriptive changes in mobility: Retail and recreation, grocery and pharmacies, and parks

Note: Relative percentage changes from the baseline day (median value from 3 Jan – 6 Feb 2020), controlling for weather conditions and time-location-fixed effects. SoE = State of Emergency; Mean percentage change from baseline with shaded areas representing 95%CI among 47 prefectures. The SoE periods denote time ranges where the declaration took effect in at least one prefecture.



home (or stopped their businesses), and generally spent more time at home. However, the trends were found to have become more unstable during the succeeding SoEs.

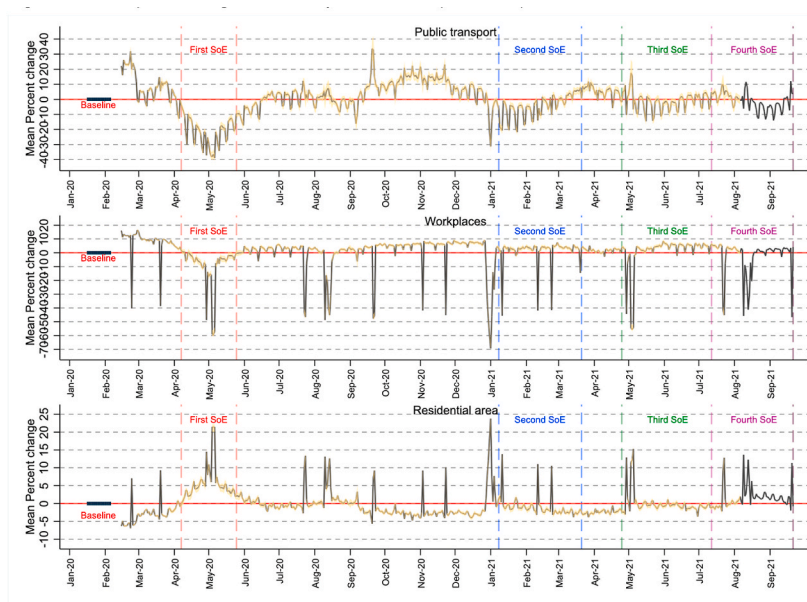
#### 4.2. SoE and mobility

Table 2 illustrates the mobility changes associated with the SoE for retail and recreation spaces as well as residential areas. Overall, visits and the duration of stay at places related to retail and recreation declined during all SoE declarations, and demonstrated further decline as time passed. However, the trends (i.e. downward-convex curves) suggested that when the SoE lasted too long, it lost its effectiveness. For instance, the mobility index for retail and recreation declined by 12.88 percent-points (95% confidence interval [CI]:  $-13.77$  to  $-11.99$ ) overall during SoEs in comparison to non-SoE periods. The index demonstrates an immediate drop after the declaration of the SoE by 10.10 percent-points (95%CI:  $-10.95$  to  $-9.26$ ) and a further gradual decline (beta:  $-0.31$ , 95%CI:  $-0.38$  to  $-0.25$ ). When the quadratic time trend was considered, the mobility index gradually increased by 0.03 percent-points (95%CI:  $0.02$ – $0.03$ ) while declines in the initial periods of the SoE remained unchanged. A similar trend was observed for other outside-the-home mobilities for groceries, pharmacies and parks (Appendix Table 1).

Additionally, people tended to use public transport (beta:  $-15.31$ , 95%CI:  $-16.65$  to  $-13.96$ ) less, spend less time at workplaces (beta:  $-6.72$ , 95%CI:  $-7.98$  to  $-5.47$ ), and more time at home (beta:  $4.45$ , 95%CI:  $4.02$  to  $4.88$ ) during the SoE in comparison to non-SoE periods (Table 2 and Appendix Table 2). The mobility index demonstrates an immediate drop by 12.59 percent-points (95%CI:  $-14.04$  to  $-11.13$ ) after the declaration of the SoE and 4.41 percent-points (95%CI:  $-5.58$  to  $-3.23$ ) for public transport and workplaces, with a further gradual decline (beta:  $-0.31$ , 95%CI:  $-0.38$  to  $-0.23$ ; beta:  $-0.26$ , 95%CI:  $-0.33$  to  $-0.20$ , respectively). In contrast, there was a 3.37 percent-points (95%CI:  $2.94$  to  $3.80$ ) increase for residential areas, with a further gradual increase (beta:  $0.12$ , 95%CI:  $0.09$  to  $0.16$ ). With regard to the quadratic time trend, the mobility for public transport and workplaces increased while outdoor mobilities decreased as the time passed.

#### 4.3. Mobility during the first, second, third, and fourth SoE

Table 3 presents the differences in mobility changes for retail and recreation spaces and residential areas between all four SoEs. Overall, while the mobility for retail and recreation spaces declined during the first (to a larger magnitude) and second SoE, the decline in mobility during the third and fourth SoEs were less significant. Although drops by 19.40 and 10.84 percent-points in retail and recreation space mobility were observed during the first and second SoE, respectively, decline by only 3.26 and 4.60 percent-points were found in the third and fourth SoEs. Moreover, the time trends during each SoE were inconsistent. The time trends on the mobility



Note: Relative percentage changes from the baseline day (median value from 3 Jan – 6 Feb 2020), controlling for weather conditions and time-location-fixed effects. SoE = State of Emergency; Mean percentage change from baseline with shaded areas representing 95%CI among 47 prefectures. The SoE periods denote time ranges where the declaration took effect in at least one prefecture.

**Fig. 2.** Descriptive changes in mobility: Public transport, workplaces, and residential area

Note: Relative percentage changes from the baseline day (median value from 3 Jan – 6 Feb 2020), controlling for weather conditions and time-location-fixed effects. SoE = State of Emergency; Mean percentage change from baseline with shaded areas representing 95%CI among 47 prefectures. The SoE periods denote time ranges where the declaration took effect in at least one prefecture.

**Table 2**

SoE and human mobility: Retail and recreation and residential area.

Model	Retail and recreation			Residential area		
	(1)	(2)	(3)	(1)	(2)	(3)
Since observation (day)		0.11** (0.10, 0.11)	0.09** (0.07, 0.10)		-0.02** (-0.02, -0.02)	-0.01** (-0.02, -0.01)
Since observation <sup>2</sup> (day)			0.00** (0.00, 0.00)			-0.00** (-0.00, -0.00)
SoE	-12.88** (-13.77, -11.99)	-10.10** (-10.95, -9.26)	-7.94** (-8.77, -7.12)	4.45** (4.02, 4.88)	3.37** (2.94, 3.80)	2.67** (2.23, 3.12)
SoE days		-0.31** (-0.38, -0.25)	-1.27** (-1.43, -1.11)		0.12** (0.09, 0.16)	0.43** (0.35, 0.52)
SoE days <sup>2</sup>			0.03** (0.02, 0.03)			-0.01** (-0.01, -0.01)
COVID-19 cases (Last week: 100)	0.09 (-0.04, 0.21)	0.02 (-0.04, 0.09)	-0.09** (-0.13, -0.06)	-0.01 (-0.05, 0.03)	0.01 (-0.01, 0.03)	0.05** (0.04, 0.06)
Observations	27,495	27,495	27,495	27,495	27,495	27,495
R-squared	0.75	0.77	0.78	0.79	0.80	0.81
AIC	177,034	175,163	173,568	124,508	123,164	122,047

Note: The table presents coefficients with confidence intervals estimated from robust standard errors in parentheses. \*\*p < 0.01, \*p < 0.05. All models include prefecture-level fixed-effects, prefecture-by-holiday fixed-effects, prefecture-by-weekdays fixed-effects, prefecture-by-month fixed-effects, and prefecture-by-year fixed-effects, and are weighted by population size. Constants are not presented.

SoE = State of Emergency.

**Table 3**1<sup>st</sup>, 2<sup>nd</sup>, 3<sup>rd</sup>, and 4<sup>th</sup> SoE and human mobility: Retail and recreation and residential area.

Model	Retail and recreation			Residential area		
	(1)	(2)	(3)	(1)	(2)	(3)
Since observation (day)		0.07** (0.05, 0.09)	0.09** (0.07, 0.11)		-0.02** (-0.02, -0.02)	-0.02** (-0.02, -0.02)
Since observation <sup>2</sup> (day)			0.00* (0.00, 0.00)			0.00 (-0.00, 0.00)
1st SoE	-19.40** (-20.41, -18.40)	-20.63** (-21.75, -19.51)	-15.81** (-16.89, -14.72)	6.63** (5.90, 7.37)	6.85** (6.11, 7.59)	4.71** (4.27, 5.16)
1st SoE (days)		0.06** (0.02, 0.10)	-0.52** (-0.63, -0.41)		-0.01* (-0.03, -0.00)	0.18** (0.13, 0.22)
1st SoE <sup>2</sup> (days)			0.02** (0.01, 0.02)			-0.01** (-0.01, -0.00)
2nd SoE	-10.84** (-12.79, -8.89)	-8.95** (-9.96, -7.93)	-2.53** (-4.06, -1.01)	4.09** (3.27, 4.92)	2.61** (1.09, 4.13)	-1.74** (-2.48, -1.00)
2nd SoE (days)		-0.05* (-0.09, -0.01)	-0.60** (-0.70, -0.50)		0.04* (0.01, 0.08)	0.39** (0.37, 0.42)
2nd SoE <sup>2</sup> (days)			0.01** (0.01, 0.01)			-0.00** (-0.00, -0.00)
3rd SoE	-3.26** (-5.32, -1.20)	-6.40** (-8.10, -4.69)	-6.54** (-7.99, -5.08)	0.24 (-0.47, 0.95)	0.55 (-0.35, 1.44)	0.66 (-0.21, 1.52)
3rd SoE (days)		0.12** (0.09, 0.16)	0.13** (0.05, 0.20)		-0.01 (-0.03, 0.01)	-0.01 (-0.07, 0.04)
3rd SoE <sup>2</sup> (days)			-0.00 (-0.00, 0.00)			0.00 (-0.00, 0.00)
4th SoE	-4.60** (-6.33, -2.88)	-5.31** (-7.18, -3.44)	-7.22** (-9.07, -5.37)	1.99** (1.11, 2.88)	1.71** (0.89, 2.52)	2.31** (1.86, 2.76)
4th SoE (days)		0.02 (-0.02, 0.07)	0.04 (-0.08, 0.15)		0.02 (-0.01, 0.04)	0.04* (0.01, 0.07)
4th SoE <sup>2</sup> (days)			0.00 (-0.00, 0.00)			-0.00 (-0.00, 0.00)
COVID-19 cases (Last week: 100)	0.03 (-0.03, 0.09)	0.04 (-0.01, 0.10)	-0.04 (-0.15, 0.07)	0.04** (0.03, 0.06)	0.05** (0.03, 0.06)	0.06** (0.03, 0.09)
Observations	27,495	27,495	27,495	27,495	27,495	27,495
R-squared	0.78	0.79	0.73	0.82	0.82	0.78
AIC	173,965	173,119	174,981	121,463	121,186	119,189

Note) The table presents coefficients with confidence intervals estimated from robust standard errors in parentheses. \*\*p < 0.01, \*p < 0.05. All models include prefecture-level fixed-effects, prefecture-by-holiday fixed-effects, prefecture-by-weekdays fixed-effects, prefecture-by-month fixed-effects, and prefecture-by-year fixed-effects, and are weighted by population size. Constants are not presented. SoE = State of Emergency.



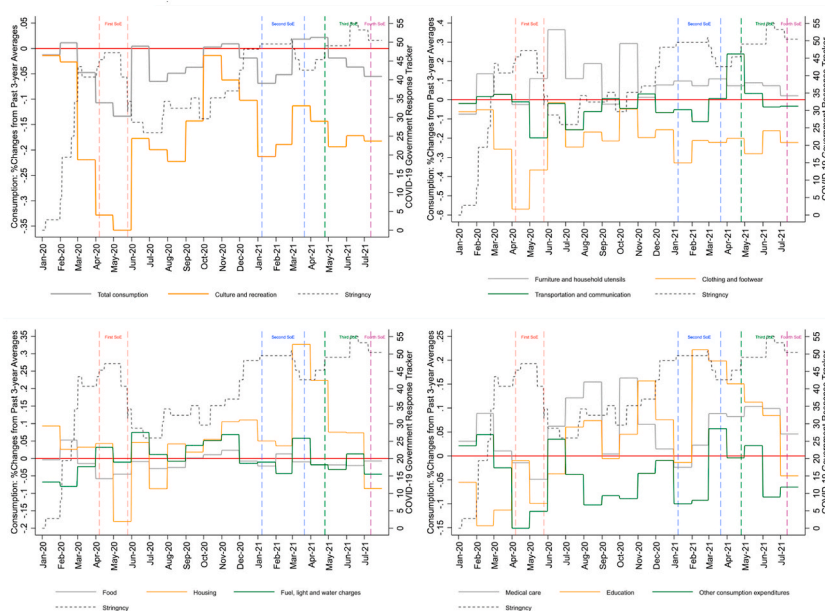
index for retail and recreation spaces increased during the first SoE (beta: 0.06, 95%CI: 0.02 to 0.10), and rose more sharply during the third (beta: 0.12, 95%CI: 0.09 to 0.16); however, it mildly declined during the second SoE (beta:  $-0.05$ , 95%CI:  $-0.09$  to  $-0.01$ ) and did not significantly change during the fourth (beta: 0.02, 95%CI:  $-0.02$  to 0.07). This pattern was also observed for other outside-the-home mobilities (Appendix Tables 3 and 4).

Increased visits and time spent at residential areas were not observed during the third SoE, although they were during the first, second, and fourth SoEs. Furthermore, the immediate increase in stay-at-home time was the highest in the first SoE (beta: 6.85, 95%CI: 6.11 to 7.59). In the second SoE, a modest initial increase in stay-at-home time by 2.61 percent-points (95%CI: 1.09 to 4.13) was followed by a gradual increase (beta: 0.04, 95%CI: 0.01 to 0.08), while no change was observed during the third SoE. During the fourth SoE, a modest increase was observed (beta: 1.71, 95%CI: 0.89 to 2.52). Biases caused by serial correlation could be a cause of concern in the current interrupted time series analysis. To assess the robustness of the findings against this, an analysis that assumed the first-order autoregressive disturbance term was additionally conducted. The analysis found that the results remained unchanged and robust (Appendix Tables 5 and 6).

#### 4.4. Government responses, mobility, and consumption

In addition to mobility changes associated with the SoE, the associations between mobility indices and the stringent government responses to the pandemic were assessed (Appendix Table 7). With stricter government responses, most of the mobility outside the home declined while residential mobility increased. In terms of containment and closure policies, the closing of schools, workplaces, public transports, stay-at-home orders were associated with declined mobility for retail and recreation spaces and the increased residential mobility (Appendix Table 8). In contrast, the associations between restrictions on gatherings and mobilities at these places had an opposite effect.

Moreover, although the availability of consumption data during the fourth SoE was limited, the per-month total consumption declined by about 13.2% and 7% in the first and second SoE respectively, compared to the average of the past three years (Fig. 3). Consumption of public transportation, culture and recreation, and clothing and footwear especially—dimensions that can be linked to activities outside the home—remarkably declined during SoEs. In sum, these mobilities declined at most by about 20%, 35%, and 57%



Note: Stringency = stringency of the Japanese government responses to the pandemic (i.e., containment and closure policies, public information campaign)<sup>12</sup>. Consumptions = per-month percentage changes during the same month in the three years prior to the COVID-19 pandemic (inflation was adjusted for using the consumer price index for each item in each month). The SoE (State of Emergency) periods denote time ranges wherein the declaration took effect in at least one prefecture.

Fig. 3. Stringency and consumption

Note: Stringency = stringency of the Japanese government responses to the pandemic (i.e., containment and closure policies, public information campaign)<sup>12</sup>. Consumptions = per-month percentage changes during the same month in the three years prior to the COVID-19 pandemic (inflation was adjusted for using the consumer price index for each item in each month). The SoE (State of Emergency) periods denote time ranges wherein the declaration took effect in at least one prefecture.

between April and May in 2020 during the first SoE; about 11%, 21%, 33% between January and March 2021 during the second SoE; and about 1%, 19%, 28% in May 2021 during the third SoE.

#### 4.5. Additional analyses

Further analyses were conducted to evaluate mobility changes associated with a quasi-SoE, a semi-state of emergency which was implemented by the Japanese government that reflected the COVID-19 conditions and their effects on healthcare capacity (Appendix Tables 9, 10, 11, 12). However, the quasi-SoE was only weakly or non-significantly associated with mobility changes to reduce human contact.

Mobility changes in the population may differ across regions based on the COVID-19 conditions. For instance, citizens in prefectures that recorded higher numbers of infections may be more likely to engage in social distancing compared to those with lower numbers. Therefore, the prefectures were classified into two groups: High and Low. A prefecture was classified as 'High' if the cumulative number of confirmed cases in that area was above the median of all prefectures within the study period. In contrast, 'Low' prefectures were those with median or below median confirmed cases. In both groups, mobility patterns were similar, which demonstrated a decline in outdoor activities and an increase in indoor behaviours after the declaration of an SoE (Appendix Tables 13 and 14). However, the post-SoE slopes suggest conflicting trends: a gradual decrease in mobility for retail and recreation spaces and an increase in residential visits and their duration were observed in the 'High' group, while the opposite trends for both locations were found in its 'Low' counterpart. With regard to non-linear time trends, identical results were found for both groups. The findings for mobility changes during each SoE for the 'High' group were almost identical to the pooled estimates for all prefectures (Appendix Tables 15 and 16).

Moreover, higher trust in the government, which was measured by the cabinet's approval ratings, may strengthen the association between the SoE and mobility in a situation wherein the citizens are requested to follow the guidelines. However, this was not evident (Appendix Table 17). Additionally, the association between vaccination rates and mobility was analysed, and vaccination rates were found to be positively associated with mobility in terms of retail and recreation spaces regardless of the declaration of an SoE (Appendix Table 18).

### 5. Discussion

This study aimed to evaluate mobility changes during the four SoEs in Japan after the distinguishment of the potential heterogeneity across each SoE and the time that passed after each declaration. The three main findings of this study are summarised as follows: First, human mobility in places outside the home effectively declined while stay-at-home time increased during the SoEs. This was also confirmed by the interrupted time-series analysis, which suggested that individuals engage in social distancing behaviours during the initial periods of the SoE but become less compliant as time passes. Second, when mobility changes during each SoE were distinguished, overall declines in mobility outside the home and increases in stay-at-home time were less obvious during the succeeding SoEs. For instance, during the third and fourth SoE, immediate decline in mobility was less significant and less common to all places. Third, the consumption level—especially for activities outside the home—sharply declined under the stringent government responses to the pandemic and decline in mobility, which suggests that strong public interventions may worsen the economy.

Even though the mobility indices were detrended by weather conditions and various prefecture-specific fixed-effects, there can be notable differences between the four SoEs. For example, the third SoE was in motion during one of the busiest holiday seasons in Japan (i.e. Golden Week), which could have motivated individuals to leave their homes. Furthermore, the fourth SoE was declared during the Olympic Games and the summer break season. Thus, the mobility level may not have been as is expected of a pandemic and an SoE, even though it might have been well-suppressed during the pre-pandemic Golden Week holidays and summer breaks. Additionally, the fear of new coronavirus variants with potentially high transmissibility rates and disease severity could have also affected population behaviours. Moreover, while the association between national-level government responses to the pandemic and mobility was analysed in this study, requests by the local government were not identical for each prefecture; this may partly contribute to the differing mobility patterns across regions. Thus, further studies are required for evaluation of this in order to obtain insights on effective responses to the pandemic.

Vaccinated individuals with greater immunity may be less willing to engage in social distancing behaviours. In fact, the findings of this study suggest that vaccination rates were associated with an increase in mobility for retail and recreation. However, the government of Japan continues to request individuals, even after they are fully vaccinated, to be compliant with social distancing. Therefore, their assisting the progress toward herd immunity against COVID-19 by the increase of vaccination, rather than reliance on non-pharmaceutical interventions, may be more efficient.

Until the majority of the population is fully vaccinated and allows for herd immunity, it is still vital to promote individual social distancing behaviours, such as the wearing of masks, disinfection, and avoidance of mass gatherings. Considering that stringent and widescale public health interventions could damage the economy, and the fact that a repetition of the same interventions could become ineffective, as demonstrated in this study, other appropriate measures need to be enforced in order to curb the virus spread. It has been observed that even less costly interventions, such as risk-communication strategies, can be considered highly effective (Haug et al., 2020). Therefore, by the utilisation of behavioural insights (Heath et al., 2019), methods to deliver directives to the population should be carefully designed to maximise their effectiveness. Also, some individuals (e.g. essential workers) need to go outside and may have to use crowded public transportation, which makes it difficult for them to maintain social distancing norms. Therefore, to ensure effective and safe public transport, basic infection controls (e.g. wearing a face mask, hand washing, and ventilation in vehicles) are

needed. Furthermore, the encouragement of working from home and staggered commutation for those who can, may help to reduce the number of commuters during peak hours in particular.

### 5.1. Limitations

Despite the significant findings of this study, there are still some limitations that should be considered. First, the Google mobility index used in the study is limited in that it does not consider an absolute figure for human mobility. Although the mobility index was detrended by weather conditions and various prefecture-specific fixed-effects, relative changes from the baseline given the narrow time range may be inappropriate, which makes interpretation difficult. Also, the Google mobility index does not include information on smaller units of regions (e.g. cities), time (e.g. daytime and night), and comparisons by sex and age. Second, the generalisability of the findings should be carefully considered. As the government's responses to the pandemic can reflect cultural and institutional differences (Shaw et al., 2020; Yan et al., 2020), the findings of this study may not be applicable to other countries. Third, as mentioned earlier, the requests by local governments varied. However, potential heterogeneity in the effectiveness of each restriction by prefecture was beyond the scope of this study and was thus not assessed. Nevertheless, implications from this study should be helpful in the highlighting of the limitations of less stringent, repeated, and prolonged public health interventions.

Since this study has some unanswered questions, further investigation is required to identify the most efficient policies to curb the virus spread. As described earlier, some previous studies evaluated effective policies to contain the outbreaks, which suggested that not only stringent interventions (e.g. lockdown and curfew) but also less costly interventions such as risk communication strategies, are effective (Haug et al., 2020). Nevertheless, the effectiveness of these policies cannot remain constant across various factors such as regions, culture roles (e.g. collective vs. individualistic), and methods, durations, and timings of the various implementations. Therefore, the identification of effective and less costly public health interventions tailored to a specific region, cultural context, and time are needed to respond to the ongoing pandemic and potential similar health crises in the future.

## 6. Conclusion

While less stringent government responses to the pandemic are effective in the promotion of social distancing by the control of human mobilities outside the home, the effectiveness may decrease if similar interventions are repeated for extended periods of time. However, upon the combination of these with other measures such as risk-communication strategies, even less costly interventions such as mild containment and closure policies can effectively curb the spread of COVID-19.

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## Author statement

The author declares no conflicts of interest associated with this study.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jth.2022.101405>.

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